Regional Studies, Regional Science

ISSN: 2168-1376 (Online) Journal homepage: www.tandfonline.com/journals/rsrs20

Looking back and forward: localised COVID-19 risks and travel dynamics

Huaxin Wang-Lu, Mihály Tamás Borsi & Octasiano Miguel Valerio Mendoza

To cite this article: Huaxin Wang-Lu, Mihály Tamás Borsi & Octasiano Miguel Valerio Mendoza (2026) Looking back and forward: localised COVID-19 risks and travel dynamics, Regional Studies, Regional Science, 13:1, 2668883, DOI: 10.1080/21681376.2026.2668883

To link to this article: https://doi.org/10.1080/21681376.2026.2668883

REGIONAL STUDIES, REGIONAL SCIENCE
2026, VOL. 13, NO. 1, 2668883
https://doi.org/10.1080/21681376.2026.2668883

Looking back and forward: localised COVID-19 risks and travel dynamics

Huaxin Wang-Lu [a], Mihály Tamás Borsi [b] and Octasiano Miguel Valerio Mendoza [c]

[a]College of Industry-Entrepreneurs and HeXie Management Research Centre, Xi'an Jiaotong-Liverpool University, Suzhou, People's Republic of China; [b]Department of Economics and Finance, IQS School of Management, Universitat Ramon Llull, Barcelona, Spain; [c]Department of Quantitative Methods, IQS School of Management, Universitat Ramon Llull, Barcelona, Spain

ABSTRACT
Balancing health and economic outcomes has been central to pandemic policy debates, yet differentiating the impacts of various intervention intensities remains challenging. To manage COVID-19 outbreaks, China implemented an area-based risk-rating system that classified small areas within cities as low-, medium- or high-risk based on local case counts. This paper examines the effects of medium- versus high-risk designations on travel behaviour during the Zero-COVID period, using a dynamic difference-in-differences approach. It further analyses the weekly travel trajectories of 368 Chinese cities during both pandemic and reopening periods within a non-linear time-varying latent factor framework. Leveraging the latest Baidu mobility data and national risk level information, our findings demonstrate that high-risk designations significantly drive shifts toward work-related trips, and the impact tends to extend beyond the affected localities. People began reacting to high-risk eight days before extensive lockdowns, and the effects persisted for approximately four weeks afterward, longer than the typical lockdown duration. Additionally, our results reveal stratified mobility dynamics, highlighting that (a) cities in western China exhibited lower resilience during the Zero-COVID period and (b) regional disparities widened during this period but gradually diminished with reopening. This study offers transferable lessons for future pandemic preparedness, demonstrating how tiered risk designations can generate responses that extend beyond targeted zones and how regional disparities in mobility evolve through crisis and recovery periods.

ARTICLE HISTORY
Received 27 February 2025
Accepted 24 April 2026

KEYWORDS
Travel behaviour; localised risk rating; difference-in-differences; dynamic factor model; Baidu mobility data; China

JEL
C33; J60; O18; R12; I18

1. Introduction

The outbreak of COVID-19 bifurcated the global response mainly into two camps: those advocating for living with COVID-19, such as the US, UK and Netherlands, and those favouring a Zero-COVID strategy, including Australia, New Zealand and China. Both approaches have their merits and challenges: as much as territories with lifted restrictions tend to see more confirmed cases and/or higher mortality rates (e.g., Cao et al., 2023; Chen & Chen, 2022), Zero-COVID policies (ZCPs) could place greater economic burdens on countries, ranging from supply-chain disruptions to reduced gross domestic product (GDP) growth (e.g., Hausmann & Schetter, 2022; Huang et al., 2023b). A growing body of literature has since debated whether government interventions were too lenient relative to the health risks (under-reaction) or too stringent relative to their economic and social costs (over-reaction) (e.g., Eslami & Lee, 2024; Hafsi & Baba, 2023; Mouhanna et al., 2023).

However, empirical studies predominantly focus on either the consequences of analogous measures across countries, typically lockdowns and stay-at-home orders (e.g., Brussevich et al., 2022; Caro et al., 2022; Palomino et al., 2020), or binary comparisons between distinct approaches, such as lockdowns versus social distancing (e.g., James et al., 2020; Yang et al., 2020, 2021). Differentiating the impacts of intervention deployed in a progressive manner has been largely overlooked. Yet, in practice, disease control in both camps often involves a combination of adaptive measures that vary in intensity and focus over time, a strategy that helps minimise health losses while maintaining economic production. In this vein, the COVID-19

CONTACT Huaxin Wang-Lu huaxin.wanglu@gmail.com
Supplemental data for this article can be accessed online at https://doi.org/10.1080/21681376.2026.2668883

risk-rating system, a key component of China's ZCP, provides a compelling case for analysis. This centralised framework classifies localised areas, typically as small as blocks, residential compounds or streets, into low-, medium- and high-risk, and introduces corresponding strategies to designated areas. By doing so, it allows local authorities in China to effectively combat viral spread while limiting the unintended consequences of the interventions it triggers.

Human mobility plays a vital role in both preventing viral transmission and mobilising the economy. Mobility precisely explains the initial spread of COVID-19 in China (Kraemer et al., 2020), and thus, curbing mobility can effectively reduce case growth (e.g., Fang et al., 2020; Glaeser et al., 2022). China's ZCP initially managed to support higher economic growth compared to many developed economies (Huang et al., 2023a). Its GDP growth, however, slowed to 0.4% by the second quarter of 2021. This decline was strongly linked to decreased labour mobility (Wu et al., 2023). The significant impact of mobility patterns on economic dynamics underscores the challenge of balancing health and economic outcomes (Spelta & Pagnottoni, 2021).

Therefore, our first research question is: To what extent do the differential interventions imposed by medium- and high-risk designations affect travel prioritisation, defined as the allocation of trips between essential (commuting) and discretionary (leisure) purposes, during the stringent Zero-COVID period (17 May 2021–26 June 2022)?[1] Here, we focus our analysis on intra-city travel primarily because it is more directly linked to urban economic activities (e.g., Chakraborty & Mukherjee, 2023; Liu et al., 2021) and residents' daily activities, while inter-city travel often transitions into intra-city travel when inbound passengers do not merely pass through. To be more specific, we examine changes in the shares of essential and discretionary trips within intra-city travel under policy constraints. Because the risk-rating system operates at a highly localised scale to minimise the spillover of side effects while sustaining containment, a significant citywide shift from discretionary to essential travel suggests that the interventions' suppressive effects have extended beyond the targeted infection zones.

Previous studies have explored the impacts of ZCPs on health, well-being, interpersonal trust, mobility, unemployment, housing markets and job-housing relationships, among others (e.g., Chen et al., 2023a; Fang et al., 2023; Huang et al., 2023b; Li et al., 2023; Mu et al., 2023). However, both the COVID-19 risk-rating system and travel prioritisation have been fairly understudied so far.[2] In fact, to the best of our knowledge, Gong et al. (2024) is the only paper that studies the impact of the area-based COVID-19 risk rating on a series of economic indicators, including inter-city travel intensity. However, due to the distinction in research focus, they do not distinguish between high- and medium-risk designations.

This study is therefore among the first to evaluate the COVID-19 risk-rating system, and specifically, the first to focus its influences on travel prioritisation. While the allocation of trips has been widely studied using Google or Apple mobility data, these datasets do not reflect shifts in travel preferences among the observed trips, as they measure percentage changes relative to a baseline day. Moving beyond changes in the total mobility to assess how the relative importance of different types of travel evolves provides novel insights for assessing policy impacts and targeting interventions. In particular, while the link between travel restrictions and reduced COVID-19 cases is well-established, another key policy concern is whether localised containment measures are efficiently targeted or impose excessive unintended disruption. Our analysis directly addresses this question by comparing the citywide effects of medium- versus high-risk designations on how residents shift their trips, each operating at a highly localised scale but triggering different intensities of intervention.

In addition, the COVID-19 literature to date has predominantly focused on the relationships between mobility patterns and individual characteristics (e.g., Fairlie, 2024; Hu et al., 2021; Long & Ren, 2022), travel restrictions (e.g., Fang et al., 2020; Friedson et al., 2021; Gibbs et al., 2020), COVID-19 spread (e.g., Iacus et al., 2020; Tokey, 2021), carbon emissions (e.g., Lei et al., 2022; Liu et al., 2020) and work-from-home (WFH) (e.g., Cicala, 2023; Delventhal et al., 2022). However, mobility dynamics surrounding travel trajectories, particularly alongside the transition from the pandemic to post-pandemic new normal (henceforth, the transitional period), have not been examined yet. This brings us to our second research question: How does the evolution of spatial heterogeneity in intra-city travel strength differ between the Zero-COVID period (17 January 2022–4 December 2022) and the post-reopening period (5 December 2022–26 November 2023)?[3] Notably, these two periods span nearly one year, covering the immediate time before and after the end of China's ZCP. Understanding this evolution will allow us to better evaluate disease control strategies and regional differences in life dynamics.

Building on the above discussion, we examine two hypotheses in this paper: H1: high-risk designations distort travel composition by dampening discretionary mobility more disproportionately than medium-risk designations; and H2: spatial heterogeneity in intra-city travel strength declines in the post-reopening period, following the removal of localised interventions. We adopt a dynamic difference-in-differences (DiD) approach for the first hypothesis and then apply the clustering technique developed by Phillips and Sul (2007) (henceforth, PS), which is highly effective for transition modelling, for the second. The PS method enables us to trace the relative trajectory of each city to the cross-country average in a dynamic manner. A novel panel dataset on a weekly basis, derived from Baidu Maps, the Chinese equivalent of Google Maps,[4] capturing intra-city travel behaviour in 368 cities has been created. More specifically, we use three unique indicators: intra-city travel strength, home-workplace (HW) commuting rates, and dining, leisure and recreational (DLR) travel rates. We further combine them with COVID-19 risk-level data, which is originated from the State Council of People's Republic of China's (PRC's) release.[5]

In sum, this paper contributes to four key strands of literature. First, it enriches the broader body of research on public health policies by being the first to examine the effects of the COVID-19 risk-rating system on travel prioritisation. In doing so, it complements existing studies on the appropriateness of pandemic interventions (e.g., Acemoglu et al., 2021; Fajgelbaum et al., 2021; Piguillem & Shi, 2022), on comparisons between under- and over-reaction measures, or between 'flattening the curve' and elimination strategies (e.g., Eslami & Lee, 2024; Yang et al., 2020, 2021) and on the effects of COVID-19 transmission or travel restrictions on mobility and related economic activities, including WFH (e.g., Cicala, 2023; Delventhal et al., 2022; Fang et al., 2020). Second, it adds to the discourse on the distribution of trips under (post-)pandemic, such as the preference for essential over non-essential trips or individual travel modes over public transportation (e.g., Albalate et al., 2022; Canina & McQuiddy-Davis, 2020; Padmakumar & Patil, 2022), by being the first study looking into how residents prioritise different types of travel.

Third, it advances the spatiotemporal mobility research (e.g., An et al., 2023; Hu et al., 2021; Jiao et al., 2022; Tokey, 2021; Xin et al., 2022), an area that remains extremely scarce in the literature, by being the first to analyse and compare the changing regional differences in human mobility around the transitional period.[6] Lastly, this paper builds upon the growing body of works that applies the PS approach to assess different aspects of convergence (e.g., Erfurth, 2024; Gutiérrez-Romero, 2021; Valerio Mendoza et al., 2022). Unlike those prior applications, which have largely focused on long-term trends, this study is the first to adapt this sophisticated econometric technique to analyse short-term variations in regional patterns on a weekly basis.

The remainder of the paper is organised as follows. Section 2 describes the data. Section 3 introduces the methods used in this study. Section 4 presents the DiD and spatiotemporal results. Our discussions and conclusions are given in Section 5.

2. Data description

2.1. Baidu mobility data

Intra-city mobility data are retrieved from Baidu Qianxi, a programme launched in 2014 built on Baidu Maps' location-based service (LBS). As one of the most popular web mapping applications in China with 130 billion real-time records of location service requests per day, over 500 million people using its AI-powered voice assistant and supporting more than 500,000 mobile apps to locate their users, it enables Baidu Qianxi to precisely trace and outline population movement within and between cities and provinces on a daily basis.

Although the construction details have not yet been released to the public, Baidu mobility data have been a key data source for studying contagion models of COVID-19 and increasingly used in recent research (see Chen et al., 2023b; Fang et al., 2020; Gibbs et al., 2020; Huang et al., 2022; Liu et al., 2021; Mu et al., 2023).[7] Notably, since Baidu data are anonymised and aggregated, we cannot directly identify individual travel purposes. For example, if a person works in a restaurant but does not mark their workplace on Baidu Maps and is not detected by Baidu's algorithms, their commutes will be recorded as DLR trips. However, such misclassification typically occurs in one direction: service workers with irregular hours at recreational establishments may be misclassified as DLR travellers. In contrast, true leisure travellers are rarely misclassified as HW, as they seldom visit office zones on a regular basis.

To analyse mobility dynamics, normalised values of the weekly intra-city travel strength, HW and DLR travel (indexation) outcomes are considered.[8] A summary is given as follows:

$$N = \frac{v - min(v)}{max(v) - min(v)}$$

where v is the original numeric value and N is the normalised outcome.

- Intra-city travel strength index: accounts for the average ratio of the number of people with trips in the city to the total population in the city from Monday to Sunday.
- HW commuting index: accounts for the average share of home-workplace trips in the city from Monday to Sunday. A destination is classified as a workplace if a user explicitly labels it as such on Baidu Maps. Additionally, Baidu's algorithms may identify workplaces by analysing users' spatiotemporal patterns and contextual information (e.g., travel time, length of stay and travel frequency).
- DLR travel index: accounts for the average share of dining, leisure and recreational trips in the city from Monday to Sunday. Trips that do not meet the workplace or home criteria are categorised into the DLR index, based on destinations typically associated with consumption and recreation (e.g., restaurants, malls, entertainment venues).

In other words, the rates of DLR and HW travel are almost inversely related. An increase in one indicator corresponds to a decrease in the other, irrespective of changes in overall travel volume. Therefore, we interpret the relative changes captured by our measures as average shifts between the two travel behaviours.

2.2. COVID-19 risk-level data

The COVID-19 risk-level data are collected from the website of the State Council of PRC and compiled on a daily basis with 366 prefecture cities.[9] For each city or equivalent administrative unit, there are three indicators recording whether it had low-, medium- and high-risk areas, respectively, in terms of the COVID-19 risk-rating system. localised areas that never have confirmed cases or do not have new confirmed cases in the last 14 consecutive days are deemed as low-risk areas. Medium-risk areas are those that have no more than 50 confirmed cases and no clustered outbreak in the last 14 consecutive days. Accordingly, when there are more than 50 confirmed cases or a clustered outbreak, high-risk will be assigned.[10]

Among the three levels, low-risk areas were the regions with basic preventive measures, such as wearing masks and body temperature testing in public areas. More measures including quarantine were introduced to medium- and high-risk areas, while the latter underwent more stringent containment, including the shutdown of all the places that are populated and with high population mobility, such as theatres, libraries, public transportation, gyms, shopping malls, supermarkets, etc., break of elective operations in hospitals, and stopping risky population (medical workers, cleaners, couriers, migrants and service staff, among others) from working in high-risk areas. A detailed summary of the risk rating system and associated interventions is provided in Table 1.

We aggregate the risk-level data into weekly frequencies and employ daily data as robustness checks. We base our DiD analysis on HW and DLR travel, respectively. These two measures can relate to different economic activities, with DLR travel more specific to the services sector. Thus, we define the medium- or high-risk indicator to be 1 if the city has at least one medium- or high-risk area during Monday–Friday, and 0 otherwise. In other words, if a medium- or high-risk area appears on Saturday or Sunday, the indicator will be coded 1 only from the following week. We choose Friday as the cutoff point because it usually divides the time between commuting for work and hanging out for recreational purposes. As mentioned before, when this indicator equals 1, we interpret it as there is an official designation as medium or high COVID-19 risk in the city.

Table 1. Overview of China's COVID-19 risk rating system.

Risk				
Level	Criteria	Key Measures	Duration	Scale
Low	No confirmed cases in the last 14 consecutive days	Mask mandates, temperature testing, health QR code monitoring	Maintained as long as no new cases	Default status
Medium	At least 1 but no more than 50 confirmed cases and no clustered outbreak in the last 14 consecutive days	All low-risk measures, plus: targeted quarantine (cases/contacts), community-wide nucleic acid testing, capacity and gathering restrictions in public venues, localised movement control	Risk designations updated dynamically on a 14-day rolling basis	Typically residential compounds and streets
High	More than 50 confirmed cases or a clustered outbreak within the last 14 days	All medium-risk measures, plus: strict stay-at-home orders, multi-round mass testing, mandatory closure of all non-essential venues and public transport, cessation of elective hospital operations	Risk designations updated dynamically on a 14-day rolling basis	Typically apartment blocks and building units

Note: This table presents key measures distinguishing risk levels. See Joint Prevention and Control Mechanism of the State Council (2021) for complete details.

We summarise all the variables in Table A1 in the online supplemental data, which reveals that the average intra-city travel strength during the Zero-COVID period was slightly greater than after the formal reopening.[11] Further, commuting rates are, on average, considerably higher than the rates for DLR travel, indicating that people prioritised work-related trips during the studied period. Lastly, within our sample, 50 cities have high-risk areas, 81 cities have only low- and medium-risk areas without any high-risk zones, and 235 cities have never experienced high or medium-risk designations.

2.3. COVID-19 cases and weather data

Additional variables used in this study include the number of confirmed COVID-19 cases and deaths from Dingxiangyuan (a popular healthcare digital platform in China), as well as temperature and precipitation data retrieved from the Global Historical Climatology Network of the National Oceanic and Atmospheric Administration.

3. Methodology

3.1. DiD identification

To test our first hypothesis, two DiD estimators are employed. Specifically, we assess the effects of official designation as medium or high COVID-19 risk on travel prioritisation. First, we utilise a traditional two-way fixed effects (TWFE) estimator to examine the relative change in outcome variables, i.e., DLR and HW travel, between the treated and control groups. The baseline specification is as follows:

$$Y_{it} = \beta Risk_{it} + \alpha X_{it} + \mu_i + \theta_t + \epsilon_{it} \tag{1}$$

where $Risk_{\mathrm{it}}$ is a binary variable equal to 1 if any locality within city i is classified as a medium- or high-risk area at time t, and 0 otherwise; X_{it} are control variables, i.e., the confirmed COVID-19 cases and deaths, temperature, and precipitation;[12] μ_i is prefecture city fixed effects; θ_t is time fixed effects. In brief, 80 cities with at least one medium-risk area and 50 cities with at least one high-risk area are categorised into treatment groups. In contrast, cities that never have medium- and high-risk areas throughout the studied period form the control group. The assignment to the treatment and control groups is fixed. It should also be noted that the cities in the two treatment groups do not overlap. When medium risk is considered as the treatment, cities that have reported high-risk areas are excluded. Once cities are classified into the high-risk treatment group, to capture the dynamics of longer-term effects, they are not allowed to switch out of the high-risk group or be reclassified into the medium-risk group.

The fundamental assumption for the treatment is that the enforcement of Zero-COVID measures is not driven by unobservable factors that could systematically differentiate studied outcomes between cities with and without high-risk (medium-risk) areas. This assumption is untestable as a counterfactual scenario is unavailable. However, we can assess the plausibility of this assumption by performing an event study approach to examine whether parallel trends assumption is satisfied before the treatment starts:

$$Y_{it} = \sum_{k=-10}^{-2} \beta_k Risk_{it}^k + \sum_{k=0}^{20} \beta_k Risk_{it}^k + \alpha X_{it} + \mu_i + \theta_t + \epsilon_{it}$$

Where $Risk_{it}^{k}$ denotes the treatment status of city i at k periods relative to period t. k = −1 is excluded as the dynamic effect is compared to the period immediately before the treatment starts. The parameter of interest here is β_{k}, which estimates the effect of the assigned intervention k periods after or before the appearance of medium- or high-risk areas.

Then, to further address treatment effect dynamics and heterogeneity, we turn to Callaway and Sant'Anna's (2021) DiD with multiple periods estimator.[13] It also enables us to use a varying base period in our estimation for pre-treatment periods, in contrast to a universal base period inherent to the traditional event study approach. The differences in results of pre-treatment periods between two types of base period do not change the conclusion about whether parallel trends assumption is violated or not, but a varying base period is helpful for detecting violations of no anticipation assumption (see Callaway, 2021; Roth, 2024). In contrast, in post-treatment periods, the base period is the period right before the implementation of treatment in both cases.

In this study, we expect a one-week anticipatory behaviour when employing the high-risk indicator as the treatment,[14] because alongside seeing the increasing confirmed COVID-19 cases updated by the Chinese government day by day, residents and organisations were able to and very likely to make predictions about what might shortly happen and react to the foreseen implementation of containment measures. In fact, Gong et al. (2024) identifies a three-day anticipation period for inter-city travel behaviours. Since intra-city mobility is likely to be more sensitive and responsive than inter-city mobility to the emergence of risky areas, we expect a four- to five-day anticipation period when considering medium risk as the treatment. In the case of high-risk, this period might extend by an additional two to three days (thus, roughly a week), as residents begin reacting to the anticipated medium risk before high-risk approaches.

The group-time average treatment effect (ATT) is defined as follows:

$$ATT(g, t) = E[Travel_t(g) - Travel_t(0) | Risk_g = 1] \tag{3}$$

$Travel_t(0)$ denote the potential HW or DLR travel rates at time t if cities remain untreated throughout the studied period; $Travel_t(g)$ capture the potential outcome if cities were to be exposed to medium or high COVID-19 risk in period g for the first time. We then estimate more aggregate parameters by summarising the ATTs across different lengths of exposure (event study), $e = t - g$.

Moreover, Callaway and Sant'Anna (2021) allows for anticipatory behaviour as long as the anticipation horizon is known. Therefore, we follow their empirical strategy by changing the 'reference' period from the week immediately preceding the treatment to two weeks before the official designation as high COVID-19 risk. In the case of TWFE models, we fine-tune the 'reference' period by replacing period −1 with period −2 as the base period and exclude period −1 from the specifications (also see Butschek & Sauermann, 2024; Butts & Gardner, 2021; Sun & Abraham, 2021).

3.2. Clustering and transition dynamics

To test our second hypothesis, we employ an empirical framework developed by Phillips and Sul (2007, 2009) to study human mobility dynamics at the city level in China. While the econometric technique proposed by Phillips and Sul (2007) was originally developed with the aim to examine convergence patterns over the long run, it is equally suitable for transition modelling for shorter periods, given its non-restrictive time series properties. In particular, the main advantage of this approach over existing tests that analyse co-movements in the variables studied is that it does not depend on any stationarity assumptions, and therefore it does not require the time series to be cointegrated. In fact, it is reminiscent of an asymptotic cointegration test that does not suffer from the small sample problems and other limiting characteristics of conventional unit root and cointegration testing. This in turn allows the model to admit a wide range of transition dynamics, and moreover, the different types of city-specific individual trajectories can be visually examined.

In addition, as part of the methodology, an iterative clustering procedure enables us to endogenously identify subgroups within the panel, without assuming *a priori* club classification of cities.

Hence, we adopt the PS method to analyse human mobility and cluster Chinese cities based on intra-city travel dynamics. Specifically, we define a nonlinear time-varying factor model as

$$X_{it} = \delta_{it}\mu_t, \tag{4}$$

where X_{it} represents the log of Baidu intra-city travel strength, HW commuting rates or DLR travel rates for city i at period t. Our variable of interest can be decomposed into a common trend component μ and a time-varying idiosyncratic loading parameter δ_{it}. The latter includes information about the individual trajectory of city i relative to the common trend μ_t, and any departure of city i from this trend depends on how individual, city-specific mobility differences within the panel change over time. The loading coefficient δ_{it} thus provides a measure of the relative distance between X_{it} and μ_t.

To formulate our null hypothesis, we model the idiosyncratic factor loadings δ_{it} in a semi-parametric form, as suggested by Phillips and Sul (2007):

$$\delta_{it} = \delta_i + \frac{\sigma_i}{L(t)t^{\alpha}}\xi_{it}, \tag{5}$$

where δ_i is fixed, ξ_{it} is $i.i.d.(0, 1)$ across i but weakly dependent over t, σ_i are idiosyncratic scale parameters, and α is the decay rate, i.e., the speed at which city-specific differences decrease over time. This representation enables us to test whether $\frac{\sigma_i}{L(t)t^{\alpha}}\xi_{it} \to 0$ in Equation 5 as $t \to \infty$ for any $\alpha \geq 0$, in which case $\delta_{it} \to \delta$, suggesting that differences in mobility characteristics across cities disappear over time. Specifically,

$$H_0: \quad \delta_i = \delta \text{ for all } i \text{ and } \alpha \geq 0,$$

which is tested against the alternative:

$$H_A: \quad \{\delta_i = \delta \text{ for all } i \text{ with } \alpha < 0\} \text{ or } \{\delta_i \neq \delta \text{ for some } i \text{ with } \ \alpha \geq 0, \ \text{ or } \alpha < 0\}.$$

The null hypothesis implies common behaviour across all cities in the panel, whereas the alternative encompasses two possible outcomes: (i) the existence of city clubs, where one or more subgroups of cities get aligned in terms of mobility patterns over time, with possibly one or more diverging units and (ii) divergence of all cities in the panel.

In order to test the null hypothesis, Phillips and Sul (2007) define the following parameter h_{it}:

$$h_{it} = \frac{X_{it}}{N^{-1}\sum_{i=1}^{N} X_{it}} = \frac{\delta_{it}}{N^{-1}\sum_{i=1}^{N} \delta_{it}}, \tag{6}$$

also referred to as the relative transition path, which measures the relative departure of the loading coefficient δ_{it} of city i at time t from the cross-sectional mean. In other words, the parameter h_i traces out the individual trajectory of each city i in relation to the panel average. The transition paths of the 368 Chinese cities in our panel may either approach each other or exhibit transitory or persistent deviating patterns over the sample period studied. The null hypothesis cannot be rejected when all cities move toward the common trend, i.e., $h_{it} \to 1$ for all i as $t \to \infty$, in which case the cross-sectional variance of h_{it} decays asymptotically:

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2 \to 0 \qquad \text{as} \qquad t \to \infty.$$

Equation (7) is formally tested using the log(t) test:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log L(t) = a + b\log(t) + u_t, \tag{8}$$

for $t = [rT], [rT] + 1, \ldots, T$, where $r > 0$.[15] Specifically, we run a one-sided t-test for $\alpha \geq 0$ using the estimate $\widehat{b} = 2\widehat{\alpha}$ and heteroscedasticity and autocorrelation consistent (HAC) standard errors, and the null hypothesis is rejected at the 5% significance level if $t_{\widehat{b}} < -1.65$. If the null is rejected for the overall sample, a clustering algorithm is applied based on repeated log(t) tests and a set of criteria, in order to detect all city clubs as well as units that deviate from the rest within the panel.[16]

4. Empirical results

4.1. DiD results using weekly data

We first present the results of the dynamic effects to address our first hypothesis (that high-risk designations distort travel composition by dampening discretionary mobility more disproportionately than medium-risk designations), both with and without adjustment for anticipatory behaviour, using Equation (2), as shown in Figures 1 and B1, and Equation (3), as shown in Figures 2 and B2 (Figures B1 and B2 are in the online supplemental data). Here, the treatment groups are composed of cities with high-risk areas, while the control groups are those that maintain low-risk areas throughout our study period. Since the designation of risk ratings depends largely on the severity of COVID-19 within the region, we incorporate confirmed COVID-19 cases and deaths in each city to control for the potential heterogeneity. Besides, weather factors usually influence mobility patterns (e.g., Burdett et al., 2021; Nilsson & Backman, 2024), particularly leisure travel behaviour, such as fewer recreational trips on rainy days. Thus, we also include two covariates to account for temperature and precipitation. Here, both unadjusted pretrends indicate a violation of the no-anticipation assumption, and the period right before the onset of treatment seen in Figure B2 suggests a one-week anticipation, aligned with our expectation, and an overestimation of the results. In contrast, pre-trends displayed in Figures 1 and 2 support the parallel trends assumption and the overall trends are consistent between two methods.[17]

One might suspect that reverse causality–shifts toward work-related trips leading to the emergence of high-risk areas–could influence the results. On one hand, the adjustment for anticipation rules out this potential concern. On the other hand, considering that cities with commuting dynamics consistently higher than the national average during the studied period never experience sub-regional high-risk, official designation as high COVID-19 risk is not, at the very least, positively correlated with a higher priority given to HW travel.[18] In fact, it is quite reasonable to see that people tend to prioritise commuting over leisure travel when any localities are designated as high-risk areas, even if they themselves live outside the affected zones. This explains the relatively small magnitudes of the coefficients reported in Table 2, as our outcome variable captures travel changes at the city level, while the risk and corresponding control measures are assigned to much smaller areas.

Overall, trade-offs between the two travel behaviours start to be restored around one week later, and preferences become adequately balanced approximately four weeks after the shock. Nevertheless, the 'recovery' is not likely a result of the lifting of restrictions, as they will be operationalised for at least two weeks, but rather of the alleviation of panic spillovers.[19] This is also because the implementation of control measures *per se* cannot directly constrain citywide travel behaviours. Instead, once high-risk areas arise in cities, residents will experience panic and/or anxiety, not only due to the potential spread of viruses but also because of

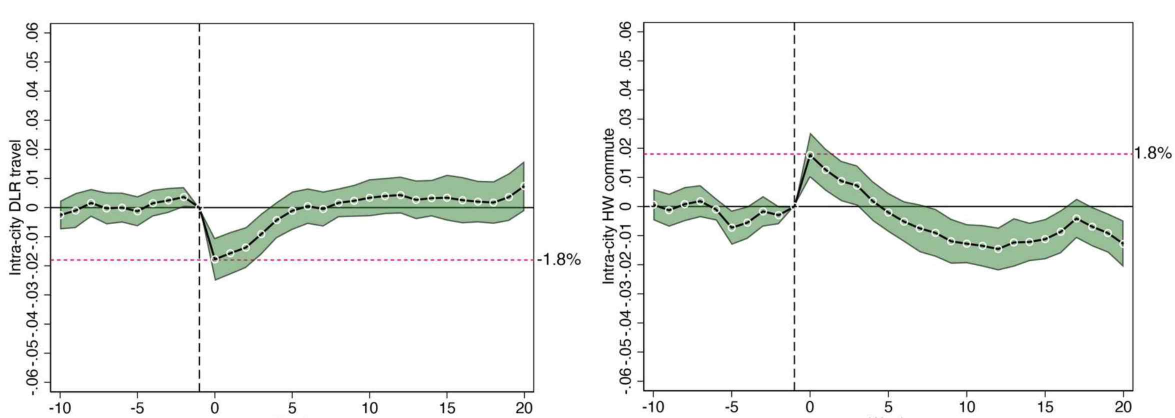

Figure 1. High-risk-based TWFE event study visualisation adjusted for 1-week anticipation.

Note: Estimates are presented with 95% confidence intervals (CIs) and a window of 10 lags and 20 leads. The pink short-dashed line showcases the point in time when the effect reaches its maximum. The plots are performed with the Eventdd command (see Clarke & Tapia-Schythe, 2021). Control variables are included.
Source: Created by authors using the Baidu mobility data and COVID-19 risk-level data (Gong et al., 2024).

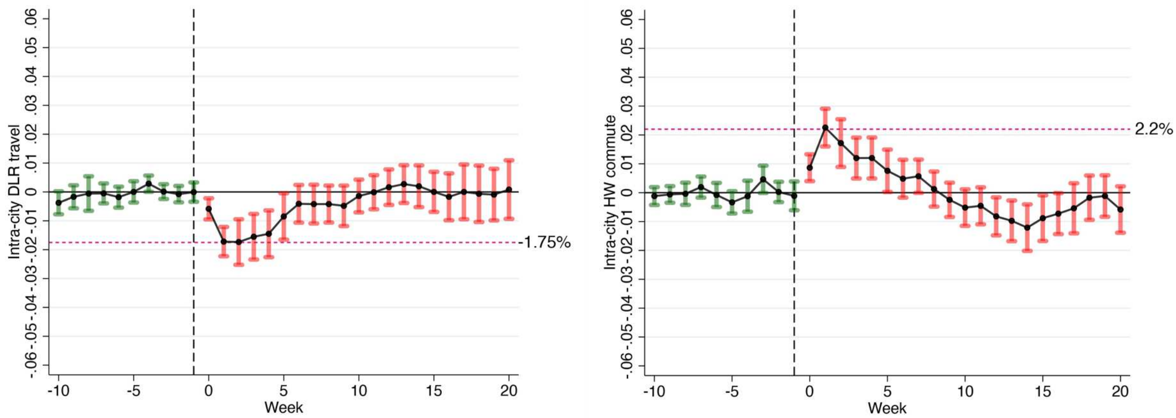

Figure 2. High-risk-based CS event study visualisation adjusted for 1-week anticipation.

Note: Estimates are presented with 95% CIs and a window of 10 lags and 20 leads based on Callaway and Sant'Anna's (2021) DiD with multiple periods estimator and event study aggregation using the varying base period. The pink short-dashed line showcases the point in time when the effect reaches its maximum. Control variables are included.
Source: Created by authors using the Baidu mobility data and COVID-19 risk-level data (Gong et al., 2024).

potential inconveniences, such as mass testing or entry restrictions to public places, they might face if they have a travel history to high-risk areas or have been in contact with someone from there in the last 14 to 21 days. Correspondingly, some residents will adjust their travel patterns, prioritising essential trips over non-essential ones, while waiting to see how the COVID-19 situation evolves, and others may follow their lead.

We now employ the medium-risk indicator as the treatment and exhibit the event-study results, estimated with Equations (2) and (3), in Figures 3 and 4. The pre-trends also suggest the presence of

Table 2. Average weekly treatment effect estimates during 17 May 2021–26 June 2022.

	(1)	(2)	(3)	(4)
High-risk				
	TWFE DLR [−2,4]	TWFE DLR [−10,20]	CS DLR [−2,4]	CS DLR [−10,20]
	−0.0126***	−0.0025	−0.0141***	−0.0045
	(0.0034)	(0.0019)	(0.0029)	(0.0033)
coeffs./mean	(12.9%)		(14.4%)	
R-squared	0.9321	0.9297	(N/A)	(N/A)
	TWFE HW [−2,4]	TWFE HW [−10,20]	CS HW [−2,4]	CS HW [−10,20]
	0.0090***	−0.0022	0.0145***	−0.0009
	(0.0033)	(0.0021)	(0.0028)	(0.0025)
coeffs./mean	(2.9%)		(4.7%)	
R-squared	0.9622	0.9603	(N/A)	(N/A)
Obs.	13,402	14,430	15,892	15,892
Medium-risk				
	TWFE DLR [−2,4]	TWFE DLR [−10,20]	CS DLR [−2,4]	CS DLR [−10,20]
	−0.0059***	−0.0021***	−0.0029	0.0038
	(0.0011)	(0.0007)	(0.0045)	(0.0066)
coeffs./mean	(6%)	(2.1%)		
R-squared	0.9326	0.9313	(N/A)	(N/A)
	TWFE HW [−2,4]	TWFE HW [−10,20]	CS HW [−2,4]	CS HW [−10,20]
	0.0087***	0.0018	0.0029	−0.0077
	(0.0018)	(0.0013)	(0.0045)	(0.0067)
coeffs./mean	(2.8%)			
R-squared	0.9624	0.9321	(N/A)	(N/A)
Obs.	13,611	15,287	17,632	17,632
City FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: Period −1 is excluded for the TWFE estimator to rule out anticipation effects, while one-week anticipation has also been adjusted for the CS method. The point estimates reported here rely on two horizons. The shorter horizon includes two lags and four leads, while the longer horizon ranges from 10 lags to 20 leads, corresponding to the visual presentation. The number of observations reported here is based on the initial estimation where all periods are involved, in other words, before applying any window restriction. The row 'coeffs./mean' provides relative effect sizes by comparing the coefficients to the sample mean. Robust standard errors are clustered at the prefecture level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Created by authors using the Baidu mobility data and COVID-19 risk-level data (Gong et al., 2024).

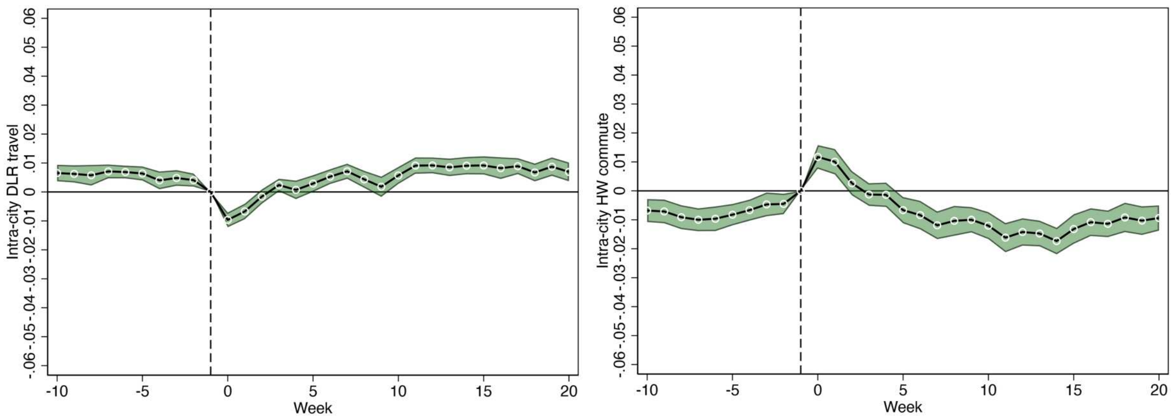

Figure 3. Medium-risk-based TWFE event study visualisation.

Notes: Estimates are presented with 95% CIs and a window of 10 lags and 20 leads. The plots are performed with the Eventdd command (see Clarke & Tapia-Schythe, 2021). Control variables are included.
Source: Created by authors using the Baidu mobility data and COVID-19 risk-level data (Gong et al., 2024).

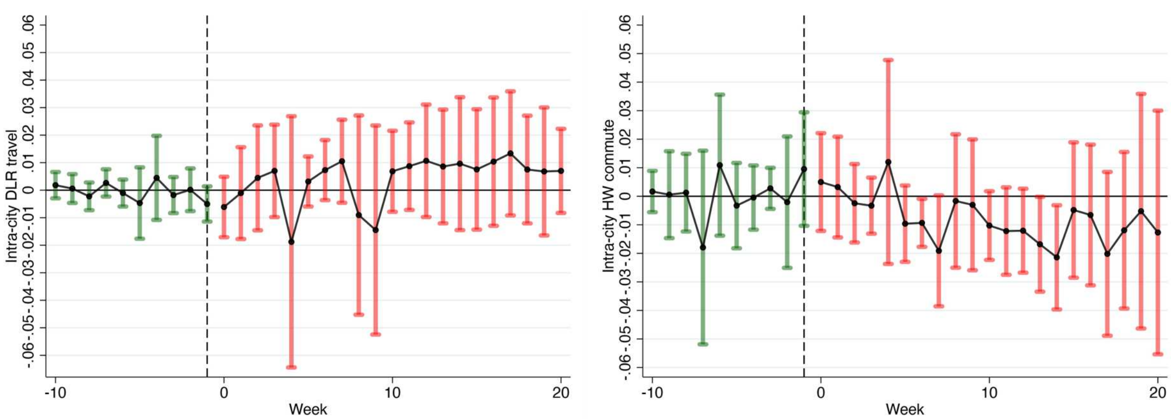

Figure 4. Medium-risk-based CS event study visualisation.

Notes: Estimates are presented with 95% CIs and a window of 10 lags and 20 leads based on Callaway and Sant'Anna's (2021) DiD with multiple periods estimator and event study aggregation using the varying base period. Control variables are included.
Source: Created by authors using the Baidu mobility data and COVID-19 risk-level data (Gong et al., 2024).

anticipation in this case. It is, however, not surprising to see the extent of anticipation observed in Figure 4 is not as strong as the high-risk case because the risk rating is usually upgraded from medium to high. As discussed later using daily data, there is a four-day anticipatory behaviour, thus a one-week adjustment is not applied here. The overall trends here reveal that the appearance of medium-risk areas does not drive remarkable changes in daily travel behaviour. The point estimates reported in Table 2 also support this finding.

Table 2 provides estimates of two horizons based on Equations (1) and (3): one as short as two lags and four leads and the other as long as 10 lags and 20 leads, to illustrate shorter- versus longer-term risk designation effects. Although the shorter-term effects adopting the TWFE method in both cases are statistically significant, after better controlling for heterogeneity in treatment timing and effects, all medium-risk-based estimates become insignificant. In contrast, the shorter-term effects based on high-risk are consistently significant, demonstrating that recreational trips are considerably de-prioritised. These results, as a whole, point out that once a high-risk sub-region has been detected, the impacts it entails, as opposed to the medium-risk scenario, on recreational activities can be quite profound.

Although the observed influence dissipates after four weeks, it has a potential to bring down many self-employed businesses and hinder the reopening of small- and medium-sized enterprises (SMEs) in the service sectors that would have otherwise remained unaffected (Chen et al., 2022). Owners' negative expectations for business demand are also found to be the primary driver for delays in reopening (Balla-Elliott et al., 2022). Indeed, China's service industry, particularly the transportation, accommodation and food services sectors, suffered the most from the outbreak (Duan et al., 2021). The self-imposed reduction in preference for DLR trips in the city, which is vital for consuming goods and services, can signal negative business prospects and contribute to the shutdown of operations in these sectors. Robustness checks and sensitivity analysis using daily data are further reported in the online supplemental data.

4.2 Intra-city travel dynamics

Figures 5 and 6 present the transition paths and clustering results of the intra-city travel strength during and after the Zero-COVID period. These results are based on the methodology described in Section 3.2 and are used to address our second hypothesis that spatial heterogeneity in intra-city travel strength declines in the post-reopening period following the removal of localised interventions. As shown, the mobility paths of the 368 cities during the pandemic form six clusters with three of them performing above the panel average. These three clusters contain 269 (73.1%) cities. Here, one notable thing is that Clusters 5–6, accounting for 29 cities (7.9%), and two divergent cities (Urümqi and Shihezi) are dropping significantly below the others, with high initial levels yet sharper declines observed for Urümqi and Shihezi. According to Figure 6(a), cities in these clusters (the least travel-intensive groups compared to the others) are mainly in Western

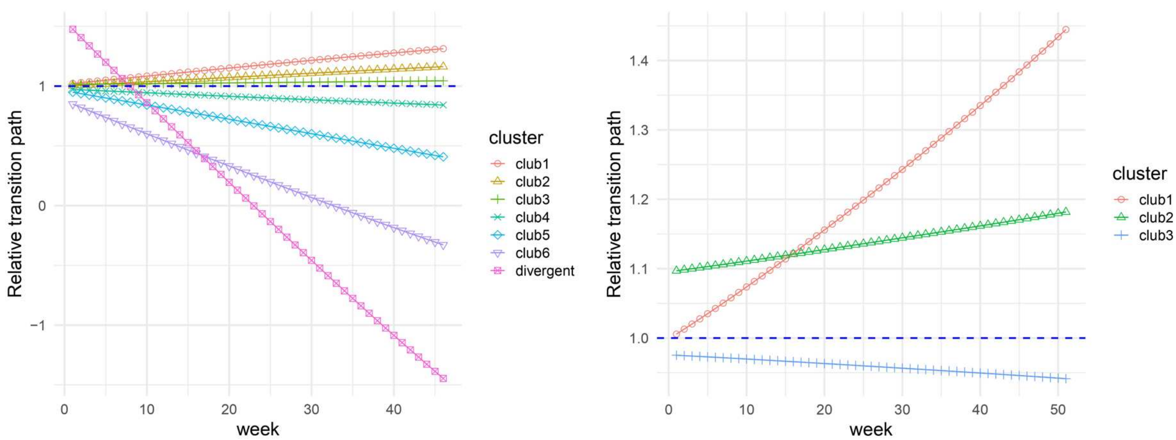

Figure 5. Transition paths of pandemic vs. post-pandemic intra-city travel strength.
Source: Created by authors using the Baidu mobility data.

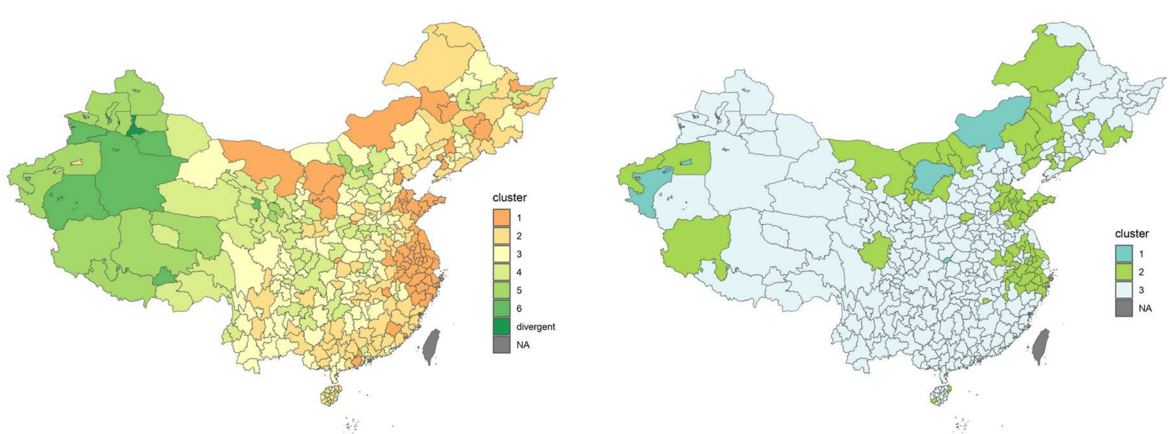

Figure 6. Spatiotemporal results of pandemic vs. post-pandemic intra-city travel strength.
Source: Created by authors using the Baidu mobility data.

China, particularly Gansu, Qinghai, Tibet and Xinjiang. These provinces are likely to see a wider range of mobility-dependent activities less active.[20]

In contrast, cities in Clusters 1–2 are mostly concentrated on coastal areas, especially the Yangtze River Delta, Pearl River Delta and Fujian, the most economically developed regions in China. This implies the remarkable division between Western China and the rest of the country seen in Figure 6(a) is related to regional economic (dis-)advantages. In other words, the pandemic appears to have smaller effects on economic activities, which rely heavily on intra-city mobility, in more-developed regions, coincident with worsening regional disparities during the pandemic found in a body of literature (e.g., Bárcena-Martín & Cantó, 2025; Brown & Ravallion, 2023; Dasgupta & Murali, 2024).

Although reasons behind lower mobility could substantially vary across cities, we can draw some common behaviours from visualising the average intra-city travel strength for each cluster. As demonstrated in Figure B6(a) in the online supplemental data, intra-city mobility decreases more substantially and persistently in Clusters 5–6 and the divergent cohort, compared to Clusters 1–4, since around 7 August 2022. We further plot the daily new confirmed COVID-19 cases in China from 1 July 2022 to 23 December 2022 (the last date of update) in Figure B7 in the online supplemental data. A surge in cases appears right after 1 August 2022 and continues to climb until the date of formal reopening. Therefore, a plausible explanation here is that less travel-intensive cities during the Zero-COVID period are those less resilient to and/or more panic about the spread of COVID-19.

Conversely, after the reopening, only three clusters are detected for the intra-city travel strength across China, with Cluster 3 slightly decreasing below the average. As Figure 6(b) reveals, the travel dynamics become much flatter and more homogeneous, with 287 (78%) cities in Cluster 3. Interestingly, not only do most western cities fall into this group, but coastal cities in the Pearl River Delta and Fujian are now in Cluster 3. Likewise, even though some cities in Jiangsu and Zhejiang are in Cluster 2, Shanghai is included in Cluster 3. It may raise concerns that such a homogeneous pattern reflects a widespread economic downturn following the reopening. Figure B6(b) in the online supplemental data reveals three key points on this matter: firstly, Cluster 3 does not experience huge fluctuations but rather presents a relatively smooth pattern, and its average value does not differ much from the average of Clusters 1–2 during the Zero-COVID period; secondly, Clusters 1–3 begin to deviate from each other around 15 January 2023, one week before the Chinese New Year, with Cluster 1 continuing to spike since 29 January 2023, the first week back from the holidays. These point out a potential relationship between the intensity of intra-city trips and the Spring Festival Travel Rush (Chunyun)–the movement of migrant workers may partly drive the differences. Thirdly, the distances further enlarge during early July to early September, peaking around 6 August 2023, which marks a peak tourist season as the summer break of Chinese schools falls exactly within this time frame.

Given all that, our comparisons illustrate that a higher intensity of intra-city trips is likely to be correlated with certain economic activities, particularly like tourism services, while a lower intensity elsewhere should not be simply regarded as a signal of lower levels of economic vitality, except for cities with persistent low mobility (mainly in western China). Instead, there might be a long-term increase in working from home or hybrid modes, particularly in economically developed regions where industries have a greater capacity to offer remote jobs, resulting from organisations' adoption of relevant policies since the pandemic (e.g., Bamieh & Ziegler, 2022; Delventhal et al., 2022; Garrote Sanchez et al., 2021). In addition, the stronger similarity in post-pandemic travel dynamics suggests that the amplified regional disparities, at least in mobility-dependent activities, may diminish as China adapts to the new normal.

5. Discussion and concluding remarks

Utilising a unique panel built on the latest Baidu mobility data and national COVID-19 risk-level data, this study examines the effects of different risk designations on travel prioritisation. It further analyses weekly travel trajectories across 368 Chinese cities during the Zero-COVID and reopening periods. Our primary findings based on DiD estimation introduced in Section 3.1 confirm our first hypothesis by showing that residents tend to prioritise work-related trips over leisure ones when any locality in the city is identified as high-risk. These shifts toward commuting last for nearly four weeks and the impact tends to extend beyond designated zones, likely due to panic spillovers, herding behaviour and pre-emptive restrictions imposed on contacts. Although mobility changes in small localities, typically blocks or streets, would intuitively seem unlikely to affect citywide travel, we observe a strong citywide effect following high-risk designations. In contrast, despite medium-risk counties being three times as numerous as high-risk counties in our data, we observe no significant impact of medium-risk designations on travel behaviour. This contrast suggests that the response is driven not by the prevalence of risk designations but by the sharp escalation in intervention intensity that accompanies the high-risk label, which produces spillovers well beyond the targeted localities. Importantly, this does not imply that residents responded irrationally: heightened caution when a high-risk designation is announced could be entirely reasonable given the severity of the associated restrictions. Rather, the mismatch we identify is between the policy's localized design intent and thebroader citywide dynamics.

These findings highlight an important trade-off for policymakers designing tiered intervention systems. On one hand, stringent high-risk measures help rapidly contain outbreaks and protect public health. On the other hand, our results show that these measures trigger citywide contractions that disproportionately affect consumption-based service sectors for weeks beyond the intervention period. The medium-risk bundle of measures, including targeted testing, contact tracing and localised restrictions, did not produce such spillovers, suggesting it achieves more geographically contained effects. How to calibrate the boundary between these tiers involves weighing the benefits of rapid containment against the broader economic costs, a determination that requires integrating epidemiological and economic evidence, and that ultimately reflects the relative weight a society places on these competing objectives. Two notable contributions from these findings are: first, this is the first to examine the COVID-19 risk-rating system's effects on travel prioritisation, and second, the first to explore how residents prioritise different types of travel (e.g., essential vs. non-essential) during the pandemic.

We then use the clustering method introduced in Section 3.2 and find that the relative distance in intra-city mobility is decreasing within each cluster but increasing between different clusters, both during the Zero-COVID period and after its termination. However, post-pandemic travel patterns are much more homogeneous, confirming our second hypothesis. Additionally, a clear division is observed between Western China and the rest of the country during the Zero-COVID period, but not after reopening, despite persistent low mobility in various western cities. These findings elucidate that, on one hand, the pandemic tends to exacerbate regional disparities in mobility-dependent activities, while on the other hand, reopening helps to alleviate them for the majority.

These results provide a strong empirical basis for policy-making. The clear and persistent divergence between clusters recommends against a one-size-fits-all policy and supports developing policy on a cluster basis. The fact that mobility is converging within clusters suggests that tailoring local policies to each cluster's specific needs is a viable and efficient strategy. Finally, the identification of a persistently low mobility pattern in Western China underscores the necessity of allocating more resources to those areas to ensure an equitable recovery. To conclude, this analysis yields two additional contributions: first, this is the first study to analyse dynamic regional differences in mobility during the pandemic-to-post-pandemic transition, and second, the first to apply the PS approach to assess short-term variations in regional patterns on a weekly basis.

As other pandemics are likely and are predicted to happen, learning from this pandemic will help prepare the response and adaptation to future health crises (e.g., Leider et al., 2023; Morens & Fauci, 2020). The lessons from this study also extend globally. The tiered risk-rating system, for example, presents a scalable model for geographically targeted interventions in other large nations with significant regional variations, such as the United States, Brazil, India or Australia. That said, our results also reveal that high-risk designations can trigger disproportionate responses relative to the policy's localised scope, underscoring that replicating such a system requires attention to both the calibration of risk tiers and complementary communication strategies to moderate spillovers and their economic impacts. Furthermore, the finding that residents prioritise work over leisure reveals a disproportionate impact on consumption-based service sectors, an insight highly likely to be transferable across national contexts. Our analysis of regional disparities resonates with challenges worldwide, where pandemics often exacerbate existing divides, validating a recovery model where resources are intentionally allocated to less-resilient regions. Additionally, the high-frequency clustering methodology we employ could be replicated using similar mobility data sources elsewhere, enabling the real-time monitoring and adaptive policy design necessary to execute such strategies during future crises.

Ultimately, it is important to acknowledge the remaining limitations. First, we cannot capture heterogeneity in travel responses based on individuals' proximity to designated risk areas within cities. Our mobility data from Baidu are aggregated at the prefecture city level and anonymised, precluding analysis at finer geographic scales. Consequently, we treat all areas within a city uniformly when any locality receives a medium- or high-risk designation. In reality, residents closer to designated areas may respond differently, either more strongly due to perceived proximity or less uniformly depending on the size of risk zones. Future research with georeferenced mobility data at finer spatial resolution could explore how proximity shapes travel behaviour and identify the spatial decay of policy effects.

Second, trip classification in Baidu data carries inherent constraints as individual travel purposes cannot be directly verified. Misclassification can occur, particularly for service workers whose commutes may be recorded as DLR rather than HW trips, while true leisure travellers are rarely misclassified as work commuters. This may lead to underestimation of DLR reductions under risky designations. Future research with validated trip-purpose data could better capture occupational heterogeneity in responses.

Third, our aggregated data cannot capture differential responses across socio-economic groups, age cohorts or occupational categories. Residents' ability to adjust travel behaviour likely varies by income, job flexibility and remote work access. Lower-income workers may have less flexibility to reduce commuting under high-risk designations, while those with remote work options may more readily adjust their travel patterns. Future research disaggregating mobility by demographic characteristics could provide more nuanced insights into who bears the greatest policy burden and inform more equitable design.

Notes

1. China released the Protocol for Prevention and Control of COVID-19 (9th Edition) on 27 June 2022, relaxing its ZCP, following the eighth edition published on 14 May 2021. The new protocol reduced the containment duration in high-risk areas from 14 days to 7 days and relaxed other measures. Since 11 November 2022, it further merged the medium- and high-risk categories. To compare which intervention could be a more balanced approach, we exclude periods with inconsistent measures and use 17 May 2021 to 26 June 2022, as our study period.
2. US COVID-19 policies typically involved a hybrid approach that allowed for localised responses, but these measures were not consistently progressive or adaptive over time. In contrast, the centralised risk-rating system China implemented allows for a more systematic and progressive management of outbreaks.
3. One of the data sources stopped updating and providing data at the end of November 2023. Hence, the week of 20–26 November 2023, is the latest in the dataset.
4. In contrast to Google and Apple mobility data, one virtue of the Baidu mobility data is that it allows changes to be compared between provinces and cities.
5. See Gong et al. (2024) for further discussions on the risk-level data.
6. Among the very few studies related to COVID-19 in this cohort, regional differences, despite being somewhat reflected on maps, have never before been examined in a dynamic manner, nor with a comparison.
7. The data could be biased towards younger people and longer-distance trips and against underdeveloped cities or areas where Baidu Maps is somewhat less popular, such as Hong Kong and Macao.
8. As Baidu mobility data can take any numeric value greater than or equal to 0, without normalising them, it is hard to compare results between sub-samples straightforwardly.
9. In the Chinese administrative system, a 'prefecture city' is an administrative unit comprising urban districts, counties and county-level cities. Risk designations were identified at the level of specific 'localities' (e.g., residential compounds, blocks, building units). Policy implementation follows administrative jurisdiction rather than geographical proximity: designated localities are governed by their parent prefecture city, even if located near another city's boundaries.
10. This cut-off point (50 confirmed cases/clustered outbreak) is the official threshold defined by the Chinese government to trigger interventions at different levels and is adopted directly in this study as we focus on risk designations that officially triggered the actual mandatory government interventions (see Joint Prevention and Control Mechanism of the State Council, 2020). However, we acknowledge that this threshold, based on an absolute numerical measure, carries a known methodological limitation. Ideally, the threshold could take into account regional characteristics, such as the size of the local population and population density, to better reflect the true incidence rate and localised risk.

11. The intra-city travel strength index reflects relative human mobility, adjusted in proportion to the overall volume of intra-city movement, and can only be interpreted comparatively.
12. While we control for confirmed cases and deaths to account for disease severity, we acknowledge that official risk designations and voluntary behavioural responses co-evolve as part of China's pandemic response. Our estimates therefore capture the combined effect of risk designations, including both mandatory policy interventions and any amplifying behavioural responses triggered by the official signal.
13. As we use those never-treated as controls, the estimator is identical to Sun and Abraham's (2021) cohort-and-period specific estimator.
14. We wish to recap the threshold for classifying risky areas was calculated on a two-week basis, making it very unlikely to anticipate events two or more weeks ahead.
15. Phillips and Sul (2007) recommend a slowly varying function $L(t) = \log(t)$ and setting $r > 0$ on the interval $r \in [0.2, 0.3]$ for sample sizes $T \geq 100$ and $T \leq 50$, respectively.
16. The reader is referred to Phillips and Sul (2007, 2009) for a detailed description of the clustering algorithm.
17. As explained, following a body of literature on econometrics and applied economics (e.g., Butschek & Sauermann, 2024; Callaway & Sant'Anna, 2021; Sun & Abraham, 2021), we adjust the base period for both methods and exclude $t = -1$ from the dynamic TWFE specifications.
18. Empirical studies also point out that places like restaurants, gyms, hotels, cafes and religious organisations tend to be the main diffusers. In addition, the pairwise correlation rate between the treatment variable and HW travel indicator is just −0.0042.
19. Such spillover effects can even be found in adjacent cities (e.g., Gong et al., 2024; Li et al., 2024).
20. As aforementioned, population density does not influence the results as our indicators are comparable between cities.

Acknowledgements

We thank Da Gong and Andong Yan for sharing the data, and participants at the 14th International Symposium on Human Capital and Labor Markets and the CES 2023 Annual Conference for helpful feedback. All remaining errors are our own.

Author contributions

CRediT: **Huaxin Wang-Lu:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Mihály Tamás Borsi:** Conceptualization, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing; **Octasiano Miguel Valerio Mendoza:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This work was supported by the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement [grant number 838534]; and the Horizon Europe Grant Agreement [grant number 101086139].

Data availability

The Baidu data used in this study are publicly available via Baidu Qianxi, and the COVID-19 risk-level data are from Gong et al. (2024) and can be downloaded from https://github.com/dadasmash/China_COVID_Risk_Level_Dataset.

ORCID

Huaxin Wang-Lu http://orcid.org/0000-0001-5942-9475
Mihály Tamás Borsi https://orcid.org/0000-0001-7569-6207
Octasiano Miguel Valerio Mendoza https://orcid.org/0000-0001-9127-8777

References

Acemoglu, D., Chernozhukov, V., Werning, I., & Whinston, M. D. (2021). Optimal targeted lockdowns in a multigroup sir model. *American Economic Review: Insights*, *3*(4), 487–502. https://doi.org/10.1257/aeri.20200590

Albalate, D., Bel, G., & Gragera, A. (2022). Mobility, environment and inequalities in the post-covid city. *Cambridge Journal of Regions, Economy and Society*, *15*(3), 459–475. https://doi.org/10.1093/cjres/rsac021

An, R., Tong, Z., Liu, X., Tan, B., Xiong, Q., Pang, H., Liu, Y., & Xu, G. (2023). Post covid-19 pandemic recovery of intracity human mobility in Wuhan: Spatiotemporal characteristic and driving mechanism. *Travel Behaviour and Society*, *31*, 37–48. https://doi.org/10.1016/j.tbs.2022.11.003

Balla-Elliott, D., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. (2022). Determinants of small business reopening decisions after covid restrictions were lifted. *Journal of Policy Analysis and Management*, *41*(1), 278–317. https://doi.org/10.1002/pam.22355

Bamieh, O., & Ziegler, L. (2022). Are remote work options the new standard? Evidence from vacancy postings during the covid-19 crisis. *Labour Economics*, *76*, 102179. https://doi.org/10.1016/j.labeco.2022.102179

Bárcena-Martín, E., & Cantó, O. (2025). The three is of downward income mobility: A directional subgroup decomposable measure. *Review of Income and Wealth*, *71*, e12686.

Brown, C., & Ravallion, M. (2023). Inequality and social distancing during the pandemic. *The Journal of Economic Inequality*, *21*(3), 679–702. https://doi.org/10.1007/s10888-023-09590-w

Brussevich, M., Dabla-Norris, E., & Khalid, S. (2022). Who bears the brunt of lockdown policies? Evidence from teleworkability measures across countries. *IMF Economic Review*, *70*(3), 560–589. https://doi.org/10.1057/s41308-022-00165-9

Burdett, A., Davillas, A., & Etheridge, B. (2021). Weather, mental health, and mobility during the first wave of the COVID-19 pandemic. *Health Economics*, *30*(9), 2296–2306. https://doi.org/10.1002/hec.4371

Butschek, S., & Sauermann, J. (2024). The effect of employment protection on firms' worker selection. *Journal of Human Resources*, *59*(6), 1981–2020. https://doi.org/10.3368/jhr.0919-10433R1

Butts, K., & Gardner, J. (2021). {did2s}: Two-stage difference-in-differences. *arXiv preprint arXiv:2109.05913*.

Callaway, B. (2021). Universal vs. varying base period in event studies. https://bcallaway11.github.io/posts/event-study-universal-v-varying-base-period.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Canina, L., & McQuiddy-Davis, N. (2020). Pre-and post-COVID travel preferences.

Cao, X., Li, Y., Zi, Y., & Zhu, Y. (2023). The shift of percent excess mortality from zero-covid policy to living-with-Covid policy in Singapore, South Korea, Australia, New Zealand and Hong Kong Sar. *Frontiers in Public Health*, *11*, 1085451. https://doi.org/10.3389/fpubh.2023.1085451

Caro, J. C., Clark, A. E., d'Ambrosio, C., & Vögele, C. (2022). The impact of covid-19 lockdown stringency on loneliness in five European countries. *Social Science & Medicine*, *314*, 115492. https://doi.org/10.1016/j.socscimed.2022.115492

Chakraborty, T., & Mukherjee, A. (2023). Economic geography of contagion: A study of covid-19 outbreak in India. *Journal of Population Economics*, *36*(2), 779–811. https://doi.org/10.1007/s00148-022-00935-9

Chen, J., Cheng, Z., Gong, R. K., & Li, J. (2022). Riding out the covid-19 storm: How government policies affect SMEs in China. *China Economic Review*, *75*, 101831. https://doi.org/10.1016/j.chieco.2022.101831

Chen, J.-M., & Chen, Y.-Q. (2022). China can prepare to end its zero-covid policy. *Nature Medicine*, *28*(6), 1104–1105. https://doi.org/10.1038/s41591-022-01794-3

Chen, R., Zhang, M., & Zhou, J. (2023a). Jobs-housing relationships before and amid covid-19: An excess-commuting approach. *Journal of Transport Geography*, *106*, 103507. https://doi.org/10.1016/j.jtrangeo.2022.103507

Chen, Y., Li, K., & Zhou, Q. (2023b). Spatial differentiation of urban economic resilience and its influencing factors: Evidence from Baidu migration big data. *Technological and Economic Development of Economy*, *29*(2), 353–381. https://doi.org/10.3846/tede.2023.17869

Cicala, S. (2023). Jue insight: Powering work from home. *Journal of Urban Economics*, *133*, 103474. https://doi.org/10.1016/j.jue.2022.103474

Clarke, D., & Tapia-Schythe, K. (2021). Implementing the panel event study. *The Stata Journal: Promoting Communications on Statistics and Stata*, *21*(4), 853–884. https://doi.org/10.1177/1536867X211063144

Dasgupta, K., & Murali, S. (2024). Pandemic containment and inequality in a developing economy. *Economic Inquiry*, *62*(2), 837–864. https://doi.org/10.1111/ecin.13190

Delventhal, M. J., Kwon, E., & Parkhomenko, A. (2022). Jue insight: How do cities change when we work from home? *Journal of Urban Economics*, *127*, 103331. https://doi.org/10.1016/j.jue.2021.103331

Duan, H., Bao, Q., Tian, K., Wang, S., Yang, C., & Cai, Z. (2021). The hit of the novel coronavirus outbreak to China's economy. *China Economic Review*, *67*, 101606. https://doi.org/10.1016/j.chieco.2021.101606

Erfurth, P. (2024). Is income inequality converging at the regional level? Evidence from lis data. *Journal of Economic Geography*, *24*(3), 375–392. https://doi.org/10.1093/jeg/lbad029

Eslami, K., & Lee, H. (2024). Overreaction and the value of information in a pandemic. *European Economic Review*, *161*, 104624. https://doi.org/10.1016/j.euroecorev.2023.104624

Fairlie, R. (2024). The impacts of Covid-19 on racial inequality in business earnings. *Journal of Policy Analysis and Management*, *43*(1), 258–288. https://doi.org/10.1002/pam.22541
Fajgelbaum, P. D., Khandelwal, A., Kim, W., Mantovani, C., & Schaal, E. (2021). Optimal lockdown in a commuting network. *American Economic Review: Insights*, *3*(4), 503–522. https://doi.org/10.1257/aeri.20200401
Fang, G., Tang, T., Zhao, F., & Zhu, Y. (2023). The social scar of the pandemic: Impacts of covid-19 exposure on interpersonal trust. *Journal of Asian Economics*, *86*, 101609. https://doi.org/10.1016/j.asieco.2023.101609
Fang, H., Wang, L., & Yang, Y. (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-nCoV) in China. *Journal of Public Economics*, *191*, 104272. https://doi.org/10.1016/j.jpubeco.2020.104272
Friedson, A. I., McNichols, D., Sabia, J. J., & Dave, D. (2021). Shelter-in-place orders and public health: Evidence from California during the covid-19 pandemic. *Journal of Policy Analysis and Management*, *40*(1), 258–283. https://doi.org/10.1002/pam.22267
Garrote Sanchez, D., Gomez Parra, N., Ozden, C., Rijkers, B., Viollaz, M., & Winkler, H. (2021). Who on earth can work from home? *The World Bank Research Observer*, *36*(1), 67–100. https://doi.org/10.1093/wbro/lkab002
Gibbs, H., Liu, Y., Pearson, C. A., Jarvis, C. I., Grundy, C., Quilty, B. J., Diamond, C., & Eggo, R. M. (2020). Changing travel patterns in china during the early stages of the covid-19 pandemic. *Nature Communications*, *11*(1), 5012. https://doi.org/10.1038/s41467-020-18783-0
Glaeser, E. L., Gorback, C., & Redding, S. J. (2022). JUE insight: How much does COVID-19 increase with mobility? Evidence from New York and four other U.S. cities. *Journal of Urban Economics*, *127*, 103292. https://doi.org/10.1016/j.jue.2020.103292
Gong, D., Shang, Z., Su, Y., Yan, A., & Zhang, Q. (2024). Economic impacts of china's zero-covid policies. *China Economic Review*, *83*, 102101. https://doi.org/10.1016/j.chieco.2023.102101
Gutiérrez-Romero, R. (2021). Inequality, persistence of the informal economy, and club convergence. *World Development*, *139*, 105211. https://doi.org/10.1016/j.worlddev.2020.105211
Hafsi, T., & Baba, S. (2023). Exploring the process of policy overreaction: The covid-19 lockdown decisions. *Journal of Management Inquiry*, *32*(2), 152–173. https://doi.org/10.1177/10564926221082494
Hausmann, R., & Schetter, U. (2022). Horrible trade-offs in a pandemic: Poverty, fiscal space, policy, and welfare. *World Development*, *153*, 105819. https://doi.org/10.1016/j.worlddev.2022.105819
Hu, S., Xiong, C., Liu, Z., & Zhang, L. (2021). Examining spatiotemporal changing patterns of bike-sharing usage during covid-19 pandemic. *Journal of Transport Geography*, *91*, 102997. https://doi.org/10.1016/j.jtrangeo.2021.102997
Huang, C., Liu, G. G., & Zhao, Z. (2023a). Coming out of the pandemic: What have we learned and what should we learn? *China Economic Review*, *79*, 101934. https://doi.org/10.1016/j.chieco.2023.101934
Huang, L., Xie, R., & Yang, G. (2022). The impact of lockdown on air pollution: Evidence from an instrument. *China Economic Review*, *71*, 101731. https://doi.org/10.1016/j.chieco.2021.101731
Huang, N., Pang, J., & Yang, Y. (2023b). Jue insight: Covid-19 and household preference for urban density in China. *Journal of Urban Economics*, *133*, 103487. https://doi.org/10.1016/j.jue.2022.103487
Iacus, S. M., Santamaria, C., Sermi, F., Spyratos, S., Tarchi, D., & Vespe, M. (2020). Human mobility and covid-19 initial dynamics. *Nonlinear Dynamics*, *101*(3), 1901–1919. https://doi.org/10.1007/s11071-020-05854-6
James, A., Hendy, S. C., Plank, M. J., & Steyn, N. (2020). Suppression and mitigation strategies for control of covid-19 in New Zealand. *MedRxiv*, *2020-03*.
Jiao, J., Lee, H. K., & Choi, S. J. (2022). Impacts of covid-19 on bike-sharing usages in Seoul, South Korea. *Cities*, *130*, 103849. https://doi.org/10.1016/j.cities.2022.103849
Joint Prevention and Control Mechanism of the State Council. (2020). Guidance on scientifically-based prevention and control, precise policy implementation, and zone-based and grade-based approach to COVID-19 epidemic prevention and control work.
Joint Prevention and Control Mechanism of the State Council. (2021). China's protocol for prevention and control of COVID-19 (8th edition). National Health Commission of the People's Republic of China.
Kraemer, M. U., Yang, C.-H., Gutierrez, B., Wu, C.-H., Klein, B., Pigott, D. M., Group, O. C.-D. W., Du Plessis, L., Faria, N. R., Li, R., Hanage, W. P., Brownstein, J. S., Layan, M., Vespignani, A., Tian, H., Dye, C., Pybus, O. G., & Scarpino, S. V. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science*, *368*(6490), 493–497. https://doi.org/10.1126/science.abb4218
Lei, W., Alves, L. G., & Amaral, L. A. N. (2022). Forecasting the evolution of fastchanging transportation networks using machine learning. *Nature Communications*, *13*(1), 4252. https://doi.org/10.1038/s41467-022-31911-2
Leider, J. P., Yeager, V. A., Kirkland, C., Krasna, H., Hare Bork, R., & Resnick, B. (2023). The state of the us public health workforce: Ongoing challenges and future directions. *Annual Review of Public Health*, *44*(1), 323–341. https://doi.org/10.1146/annurev-publhealth-071421-032830
Li, Q., Yuan, Z., & Tao, R. (2024). The political economy of covid-19 in China. *China Economic Review*, *85*, 102143.
Li, T., Barwick, P. J., Deng, Y., Huang, X., & Li, S. (2023). The covid-19 pandemic and unemployment: Evidence from mobile phone data from China. *Journal of Urban Economics*, *135*, 103543. https://doi.org/10.1016/j.jue.2023.103543
Liu, S., Kong, G., & Kong, D. (2020). Effects of the covid-19 on air quality: Human mobility, spillover effects, and city connections. *Environmental and Resource Economics*, *76*(4), 635–653. https://doi.org/10.1007/s10640-020-00492-3
Liu, Y., Wang, Z., Rader, B., Li, B., Wu, C.-H., Whittington, J. D., Zheng, P., Stenseth, N. C., Bjornstad, O. N., Brownstein, J. S., & Tian, H. (2021). Associations between changes in population mobility in response to

the covid-19 pandemic and socioeconomic factors at the city level in China and country level worldwide: A retrospective, observational study. *The Lancet Digital Health*, *3*(6), e349–e359. https://doi.org/10.1016/S2589-7500(21)00059-5

Long, J. A., & Ren, C. (2022). Associations between mobility and socio-economic indicators vary across the timeline of the covid-19 pandemic. *Computers, Environment and Urban Systems*, *91*, 101710. https://doi.org/10.1016/j.compenvurbsys.2021.101710

Morens, D. M., & Fauci, A. S. (2020). Emerging pandemic diseases: How we got to covid-19. *Cell*, *182*(5), 1077–1092. https://doi.org/10.1016/j.cell.2020.08.021

Mouhanna, C., Tsoukala, A., & Ubasart-González, G. (2023). Policing and security in Southern Europe: How the covid-19 pandemic reaffirms pre-existing patterns. In M. Den Boer, E. Bervoets, & L. Hak (Eds.), *Plural policing, security and the COVID crisis. Palgrave's critical policing studies* (pp. 67–105). Cham: Palgrave Macmillan. https://doi.org/10.1007/978-3-031-19177-0_3.

Mu, X., Zhang, X., Yeh, A. G.-O., Yu, Y., & Wang, J. (2023). Structural changes in human mobility under the zero-covid strategy in China. *Environment and Planning B: Urban Analytics and City Science*, *50*(9), 2527–2542. https://doi.org/10.1177/23998083231159397

Nilsson, H., & Backman, M. (2024). An empirical application of herding behavior and compliance in the Covid-19 crisis. *Kyklos*, *77*(2), 428–457. https://doi.org/10.1111/kykl.12373

Padmakumar, A., & Patil, G. R. (2022). Covid-19 effects on urban driving, walking, and transit usage trends: Evidence from Indian metropolitan cities. *Cities*, *126*, 103697. https://doi.org/10.1016/j.cities.2022.103697

Palomino, J. C., Rodríguez, J. G., & Sebastian, R. (2020). Wage inequality and poverty effects of lockdown and social distancing in Europe. *European Economic Review*, *129*, 103564. https://doi.org/10.1016/j.euroecorev.2020.103564

Phillips, P. C., & Sul, D. (2007). Transition modeling and econometric convergence tests. *Econometrica*, *75*(6), 1771–1855. https://doi.org/10.1111/j.1468-0262.2007.00811.x

Phillips, P. C., & Sul, D. (2009). Economic transition and growth. *Journal of Applied Econometrics*, *24*(7), 1153–1185. https://doi.org/10.1002/jae.1080

Piguillem, F., & Shi, L. (2022). Optimal covid-19 quarantine and testing policies. *The Economic Journal*, *132*(647), 2534–2562. https://doi.org/10.1093/ej/ueac026

Roth, J. (2024). Interpreting event-studies from recent difference-in-differences methods. *arXiv preprint arXiv:2401.12309*.

Spelta, A., & Pagnottoni, P. (2021). Mobility-based real-time economic monitoring amid the covid-19 pandemic. *Scientific Reports*, *11*(1), 1–15. https://doi.org/10.1038/s41598-021-92134-x

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Tokey, A. I. (2021). Spatial association of mobility and covid-19 infection rate in the USA: A county-level study using mobile phone location data. *Journal of Transport & Health*, *22*, 101135. https://doi.org/10.1016/j.jth.2021.101135

Valerio Mendoza, O. M., Borsi, M. T., & Comim, F. (2022). Human capital dynamics in China: Evidence from a club convergence approach. *Journal of Asian Economics*, *79*, 101441. https://doi.org/10.1016/j.asieco.2022.101441

Wu, J., Zhan, X., Xu, H., & Ma, C. (2023). The economic impacts of covid-19 and city lockdown: Early evidence from China. *Structural Change and Economic Dynamics*, *65*, 151–165. https://doi.org/10.1016/j.strueco.2023.02.018

Xin, R., Ai, T., Ding, L., Zhu, R., & Meng, L. (2022). Impact of the COVID-19 pandemic on urban human mobility – A multiscale geospatial network analysis using New York bike-sharing data. *Cities*, *126*, 103677. https://doi.org/10.1016/j.cities.2022.103677

Yang, P., Qi, J., Zhang, S., Wang, X., Bi, G., Yang, Y., Sheng, B., & Yang, G. (2020). Feasibility study of mitigation and suppression strategies for controlling covid-19 outbreaks in London and Wuhan. *PLoS One*, *15*(8), e0236857. https://doi.org/10.1371/journal.pone.0236857

Yang, P., Yang, G., Qi, J., Sheng, B., Yang, Y., Zhang, S., Bi, G., & Mao, X. (2021). The effect of multiple interventions to balance healthcare demand for controlling covid-19 outbreaks: A modelling study. *Scientific Reports*, *11*(1), 3110. https://doi.org/10.1038/s41598-021-82170-y